License Plate Localization Based on Statistical Measures of License Plate Features

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***Abstract*— License plate localization is considered as the most important part of license plate recognition system. The high accuracy rate of license plate recognition is depended on the ability of license plate detection. This paper presents a novel method for license plate localization bases on license plate features. This proposed method consists of two main processes. First, candidate regions extraction step, Sobel operator is applied to obtain vertical edges and then potential candidate regions are extracted by deploying mathematical morphology operations [5]. Last, license plate verification step, this step employs the standard deviation of license plate features to confirm license plate position. The experimental results show that the proposed method can achieve high quality license plate localization results with high accuracy rate of 98.26 %.**

***Index Terms* — vehicle license plate localization, connected component analysis, standard deviation, license plate features**

I. Introduction

The car license plate recognition (LPR) is a very important application in intelligence transport system (ITS) such as traffic surveillances, toll collection systems, parking management systems and law enforcement. Usually, LPR system is divided into three processes: license plate localization (LPL), character segmentation (CS), and character recognition (CR). Among these, the LPL is considered the most important stage because the accuracy rate of CS and CR very much depends on the performance of the license plate localization.

In the past, a number of methods have been proposed for detecting car license plates. The approaches for LPL include texture based [1][2][3][4][5], edge features based [7][8][9], plate colour based [10][11] and learning based [12][13][14]. Generally, texture based is reported the less computation time and high accuracy rate. On the other hand, this method is restricted to distance and illumination [15]. Although, the accuracy rate of edge statistic based were reported with more than 90 %, the method highly depends on the distance between the camera and the vehicle. Another disadvantage is the difficulty in detecting LP in complex scenes. Colour based approach is an efficient method for license plate localization when the lighting conditions are good. However, colour feature is restricted when illumination and weather changed. Learning based techniques demonstrate a high accuracy rate but the computational time consuming in training process is high and these methods need large database for practising.

This paper presents a new texture based method for LPL. The main contribution of this study is the higher accuracy rate compared to Mendes et al. [5] which also adopts texture based LPL. Unlike [5], the novelty of this method is based on selecting the minimum standard deviations of license plate features, e.g. widths, heights and distances between borders and connected components within candidate regions. These statistics of license plate features can efficiently be used to distinguish the license plate with high accuracy.

II. Proposed Method

The proposed algorithm for LPL consists of two main stages based on those presented in [5]. The first stage is the extraction of candidate regions, which includes horizontal gradient operation for edge detection and filtering by applying morphological operation to produce candidate regions and regions adjustment.

The second is the candidate verification, which considers statistic measures of license plate features to detect the position of a license plate. The flowchart in Fig. 1 shows the algorithm on which the proposed method is based. The main contribution of this paper appears in the 'Decision among candidates' process in the diagram. The rest are based on the method presented in [5].

A. Horizontal Gradient

The aim of this step is to detecting vertical edges, which are easier to detect than horizontal edges, to create license plate region candidates [5]. An input image is processed by using Sobel vertical edge operator [17]. After this operation is deployed, vertical edges are obtained which include the vertical edges of windows, mirror, headlight, car shape, license plate borders and characters edges. All vertical edges will be used to determine the license plate's position. Fig. 2(b) illustrates the resulting image of the vertical edge detection on original image in Fig. 2(a). Then, a mean filter is used to emphasize license plate region which the mask has the same size as that of the license plate [5], see Fig. 2(c).

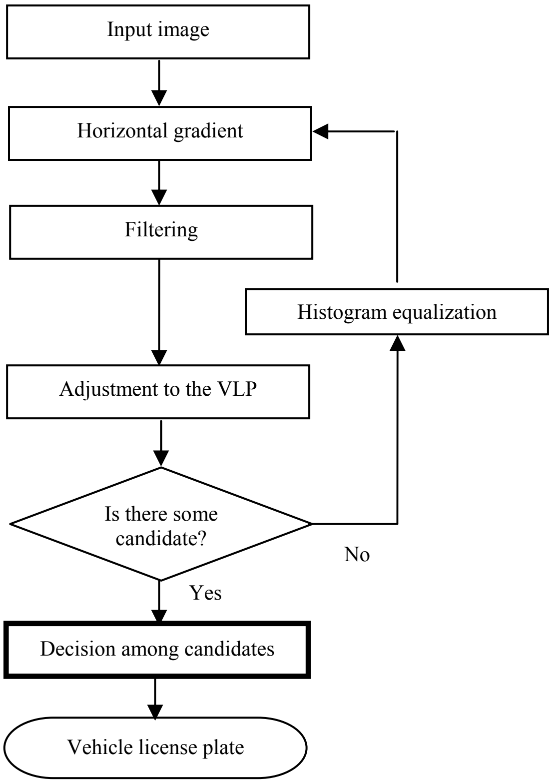


Fig. 1 The vehicle license plate localization algorithm.

B. Filtering

The objective of this step is to obtain regions potentially containing a license plate. First, noise and small regions are removed by applying morphology opening operation with structure element (SE) size equals to threshold value, MINHCHAR (minimum character height), Fig. 2(d). After that, large regions are eliminated by the opening operation with a column SE size of MAXHCHAR (maximum character height) to gain effective regions as suggested in [5], Fig. 2(e). Last, the erosion and dilation operations are applied to obtain clear border of candidate regions which may be occur during previous stage.

C. Adjust to the License Plate

This stage aims to achieve candidate regions to be the potential license plate (LP) regions. Firstly, the filtered image is converted to a binary image. The threshold value is automatically given by applied Otsu's method [16]. After binarized image, candidate regions are separated from complex background, which shows in Fig. 2(f). Secondly, removing non LP shape, the process is based on connected component analysis [5]. The potential candidate regions are preserved by following these characteristics: a) its width is greater than height; b) its width is larger than LP parameter MINWCHAR and its height is greater than minimum LP height MINHCHAR; c) LP cannot touch image boundary as suggested in [5]. Thirdly, to obtain only effective regions, intersection regions are considerably eliminated in last stage.

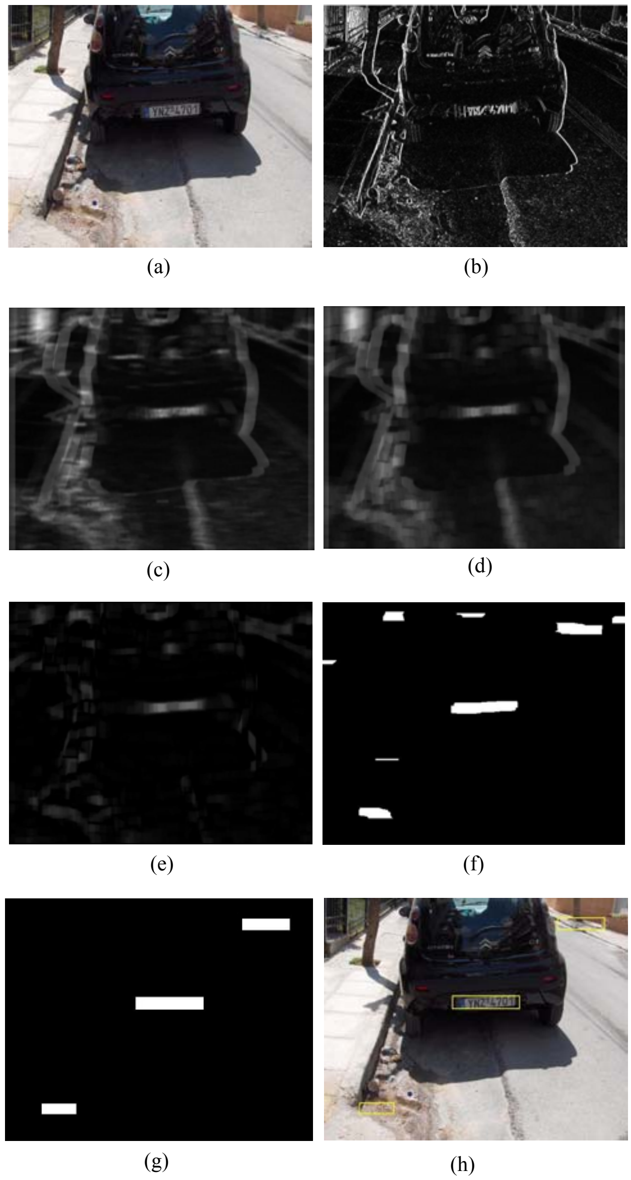


Fig. 2 Steps of the license plate localization: (a) Original image (b) Horizontal gradient (c) Mean filter on horizontal gradient (d) Small regions removed (e) Large regions removed (f) Binarization (g) Potential candidate regions (h) Candidate regions mapped location

Fig. 2(g) illustrates the potential candidate regions and Fig. 2(h) shows mapping candidates to the original image before it is sent to license plate verification stage.

D. Decision Among Candidates

The goal of this phase is to verify the LP from candidate regions. The proposed method is an improvement over Mendes et al. [5] technique by selecting the minimum standard deviations of LP features, e.g. width, height and distances between connected components and border within candidate regions, while Mendes et al. [5] presented standard deviation of gray scale distribution to accurately detect LP.

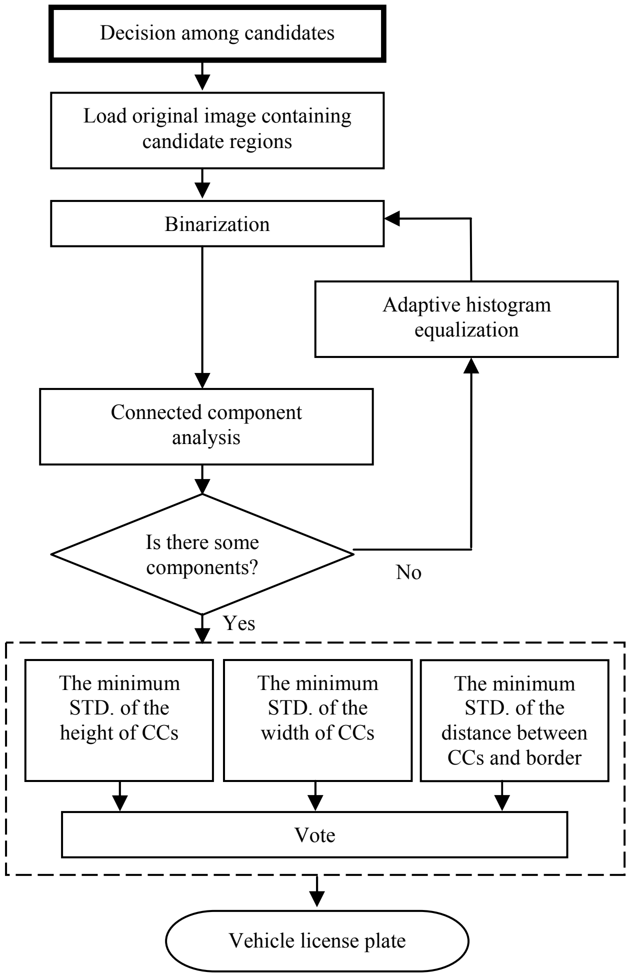


Fig. 3 The proposed algorithm decision among candidates

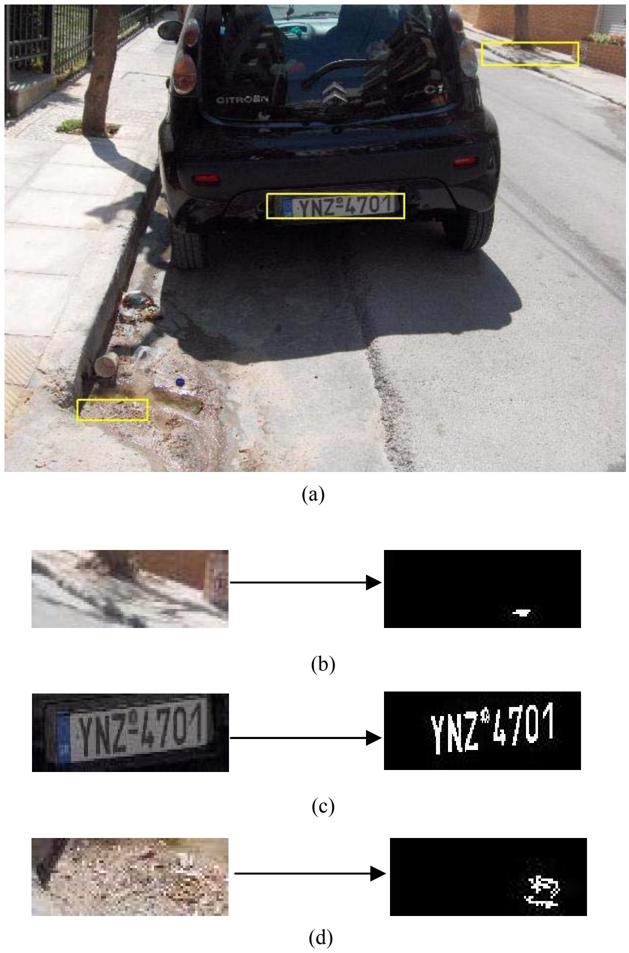


Fig. 4 Image binarization within candidate regions
(a) Original image with candidate regions
(b-d) Candidate regions with corresponding binarized image

This proposed method includes three steps: loading image, converting to binary image and LP verification. Fig. 3 shows the algorithm for making decision among candidates. Firstly, an original image containing candidate regions is imported to the process, see Fig 4(a). Secondly, candidate regions are cropped and converted to binary image by Otsu's method [16]. Fig. 4(b), 4(c) and 4(d) show the binarized image of the corresponding cropped candidate regions. Last, the region operation [17] is applied to all candidates to detect connected components (CCs) within the region. Then CCs are analysed to preserve only the effective candidate regions which have the following properties: a) the number of CCs is greater than or equal to two; b) its height is larger than the threshold, MINHCHAR; c) its width is bigger than the MINWCHAR.

If there is no candidate or all of them are discarded, adaptive histogram equalization is employed in the original image to improve the contrast. This process is performed at the beginning of binarization. If there is, still no candidate, histogram equalization is then applied [5] and the license plate detection process is repeated from the beginning.

For all CCs, the standard deviation (STD) of the widths, heights and distances between borders and CCs are calculated. Fig. 5(a) illustrates CCs within a candidate region where h_i is the height and w_i is the width of CCs and d_i is the distance of CCs to border of the region. Fig. 5(b) shows the measures of CCs within a real license plate.

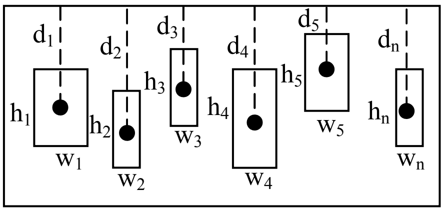
The STD of connected components' features can calculate by (1)-(3)

$$\sqrt{\frac{\sum_{i=1}^{n}\left(h_i-\bar{h}\right)^2}{n-1}} \tag{1}$$

$$\sqrt{\frac{\sum_{i=1}^{n}(w_i-\bar{w})^2}{n-1}} \tag{2}$$

$$\sqrt{\frac{\sum_{i=1}^{n}\left(d_i-\bar{d}\right)^2}{n-1}} \tag{3}$$

Since the majority of license plate characters have the same size, width, height, regularity and orientation, the proposed method, therefore, employs these features to identify a license plate from candidate regions. The candidate with the minimum STD in width, height and distance of CCs to border is classified as the license plate.



(a)

(b)

Fig. 5 connected components within candidate region
(a) Connected component within candidate region
(b) Connected components within real LP

II. EXPERIMENT RESULTS

The methods are implemented in MATLAB on an Intel Pentium Dual Core 2.10 GHz, 3 GB memory. The average runtime of one image is 59 ms. The test set of images used in the experiments is available from [6]. The set consists of 345 images and contains Greek LPs. The experiments mainly use the images to compare the proposed method to the work of Mendes et al. [5].

The success of LPL is evaluated by the values of location area (la) in (4) and the excessive area (ea) in (5) which are defined as follows:

$$la = \frac{area(r_{char} \cap r_{met})}{area(r_{char})} \tag{4}$$

$$ea = \frac{area(\overline{r_{vlp}} \cap r_{met})}{area(r_{vlp})} \tag{5}$$

where r_{char} is minimum bounding box that includes all LP characters, r_{vlp} is minimum bounding box that includes the entire LP, r_{met} is the LP region found by the method and area() is a function which returns area in

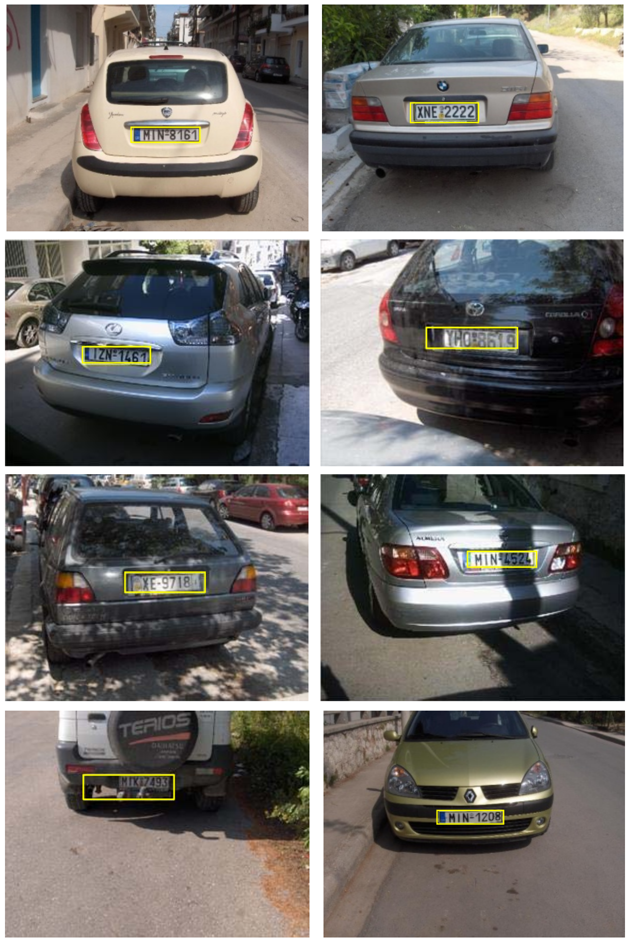


Fig. 6 the example license plate localization results

pixel of a given region. The threshold values, for instance MINHCHAR, MAXHCHAR and MINWCHAR are experimentally defined as 11, 43 [5] and 4 pixels respectively which presents the highest accuracy results. In Table I, using the same test images, the proposed method obtains better detection rates than those presented in [5] in many aspects. For example, in terms of optimum location (la>85% and ea <100%), the proposed method achieves the accuracy of 98.26%, while [5] produces 96.52%. The location error (la>85% and ea <100%), consecutive and naïve location (la>0) results are also better at 1.45%, 99.71%, compared to 2.61% and 99.13% respectively. Excessive location metric (la > 85% and ea ≥ 100%) significantly rises from 0.84 % to 24.06 %. Fig. 6 illustrates the results of license plate localization.

TABLE I
THE EXPERIMENT RESULTS

	Optimum location la > 85% and ea < 100%	**Excessive location** la > 85% and ea < 100%	**Location error l** la > 85% and ea < 100%	**“Naive” location** la > 0	**Candidate number**
Mendes et al.[5]	96.52%	0.87%	2.61%	99.13%	2.57
Proposed method	98.26%	24.06%	1.45%	99.71%	2.57

(a) (b) (c) (d)

Fig. 7 Example of error in license plate localization
(a) License plate covered by dirt (b) Blur license plate (c) license plate covered by shadow (d) low contrast license plate

However, there are some circumstances where the proposed method does not perform very accurately. They are the cases where a license plate is covered by dust, Fig. 7(a), a blur license plate with (ea <100) in Fig. 7(b), license plate is covered by shadow in Fig. 7(c) and low contrast license plate in Fig. 7(d).

CONCLUSIONS

The new LP localization method based on the statistic measure of license plate features is presented in this paper. The proposed method employs the standard deviation of the widths, heights of characters within a license plate and the distance between a border and the CCs to locate the license plate. The results show the improvement when compared to the results from the method using standard deviation of the gray level distribution described by Mendes et al. [5]. The method works well on good quality images with high contrast LPs and suitable lighting conditions. The future work will, therefore, include improving the algorithm to be able to cope with low contrast, blur images and limited lighting conditions.

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